2I3-5

Acquisition of Multilevel Adaptability for Collaboration with Humans Using a Neuro-Dynamical System

Yuxi Li*1 Shingo Murata*1 Hiroaki Arie*1 Tetsuya Ogata*2 Shigeki Sugano*1

*1 Department of Modern Mechanical Engineering, Waseda University
*2 Department of Intermedia Art and Science, Waseda University

Adequate planning is essential for intelligent robots to achieve complex task collaboration with other agents. To fulfill this adequate planning, three levels of adaptability including motion modification, action selection, and turn taking are important. We developed a hierarchically organized neuro-dynamical system that can achieve these different levels of adaptability by utilizing the multiple timescale property. The proposed system was implemented in a humanoid robot that was required to collaborate with a human partner. In both learned and unlearned situations, the robot was able to generate adequate behavior through different levels of adaptability. Experimental results demonstrate that these different levels of adaptability can be realized by a single system.

1. Introduction

Intelligent robots are expected to collaborate with human partners for achieving tasks with spatiotemporal complexity which can be dealt well by sharing roles among them. For this purpose, adequate planning is essential for these robots. We consider that adequate planning in the context of human-robot collaboration can be realized by the following three levels of adaptability: (1) motion modification [Khansari & Billard, 2011], (2) action selection [Hawkins et al., 2013], and (3) turn-taking [Awano et al., 2010]. Although these different levels of adaptability must be well-integrated, most past studies have focused on a particular aspect of these levels instead of considering the integration.

In this study, we consider to apply a hierarchically organized neuro-dynamical system called multiple timescale recurrent neural network (MTRNN) [Yamashita & Tani, 2008] as a computational framework for achieving the multilevel adaptability. MTRNNs are well-known for the ability to self-organize functional hierarchy by utilizing their multiple timescale property. We speculate that this ability can contribute to the acquisition of the multilevel adaptability. An MTRNN was implemented in a humanoid robot and the robot was required to collaborate with a human partner in a bell hitting task. Results demonstrate that the multilevel adaptability can be acquired by the single system.

2. Model

MTRNNs consist of two groups of context layers according to their timescale (Figure.1(a)). One is the fast context layer (or lower level) representing action primitives and the other is the slow context layer (or higher level) representing the sequence of the primitives. In the present study, an MTRNN is adopted for learning to generate sensory predictions, by considering its ability to deal with sequential tasks. In addition, a static vector called parametric bias (PB) is utilized as the highest-level representation to keep task sequences. It should be noted that the same task under the different environmental situations is represented by the same PB. By combining both PB information representing a task sequence and sensory inputs representing the current environmental situation, the system can achieve adequate planning.

There are two information pathways in the system. One is the top-down pathway starting from the highest-level representation of PB and finally ending at the lowest-level sensory predictions through the slow and fast context layers. The result of sensory (proprioceptive) predictions is sent to a robot as a target state to generate actions. The other is the bottom-up pathway starting from sensory inputs to the slow context layer through the fast context layer.

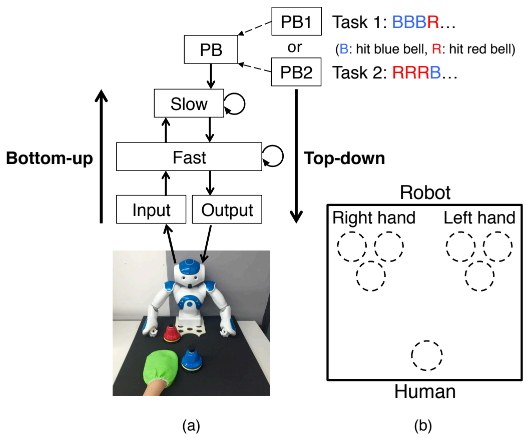

Figure 1: Structure of system.

3. Experimental Setup

A collaborative bell hitting task between a human and a humanoid robot NAO (Figure.1(a)) is considered. Two bells with different colors (red and blue) and a green glove

Contact: Yuxi Li, Department of Modern Mechanical Engineering, Waseda University, 3-4-1 Okubo, Shinjuku, Tokyo 169-8555, yuxili@sugano.mech.waseda.ac.jp

for human's hand are used in experiments. On each agent's side, one bell is located. Two kinds of collaborative task sequences are given. One of the sequences is repeating BBBR (B: hit blue bell, R: hit red bell), and the other is repeating RRRB. On the robot's side, bell positions include three fixed positions around each hand of the robot (Figure.1(b)). On the human's side, one bell position is fixed in front of him/her. In the experiments, with a shared task sequences between the human and the robot, the aforementioned three different levels of adaptability were tested. For (1) the motion modification, we set different situations by slightly changing bell positions around one of the robot's hand. For (2) the action selection, we set different situations by changing bell positions between two of the robot's hands. For (3) the turn taking, we set different situations by changing bell positions between the human and the robot.

The parameters we used for the MTRNN training were as follows: number of fast context neurons $N_F = 100$, time constant of fast context neurons $\tau_F = 2$, number of slow context neurons $N_S = 10$, time constant of slow context neurons $\tau_S = 50$, number of PBs $N_P = 2$. Data for each task with various bell positions were collected for training. The MTRNN training was conducted in an offline manner using all collected data. The testing for the multilevel adaptability of the system was conduced by implementing the trained MTRNN on the robot for collaborating with the human in actual environment.

4. Results

Figure 2 shows the testing results of the robot's vision and action during the collaboration of BBBR task sequence with a human. In the first case, the robot first hit the blue bell on its right side three times and then the human hit the red bell once. A third agent changed the bell positions from 1 to 2, and finally to an unlearned position 3 during action generation. Receiving the changes of the blue bell position of visual input in the bottom-up pathway, the prediction of the robot's arm joints was slightly changed through the top-down process. From the first case to the second case, the third agent changed the blue bell from the right to left on the robot's side. With PB in the highest level to keep achieving BBBR sequences, the change of bell position in visual input caused the change of the action selection of robot through the top-down pathway. In time step around 650, the third agent switched the blue and red bells between the robot and the human. In this case, the robot should wait for its own turn till the red bell should be hit. The visual input changed by bell switching, especially the information of collaborator's action, made the turn taking succeed through top-down pathway.

5. Conclusion

This study applied a hierarchically organized neurodynamical system called MTRNN with PB units as a computational framework for achieving human-robot collaboration. Through the top-down and bottom-up pathways of the system, the integration of different levels of adaptability including motion modification, action selection, and turn taking was able to be acquired by the single system. Currently, we used all the possible situations in the training phase. For future work, we will consider using some of situations for learning, and the others for testing. We expect that the system can also adapt to unlearned situations via its generalization ability based on learned experience.

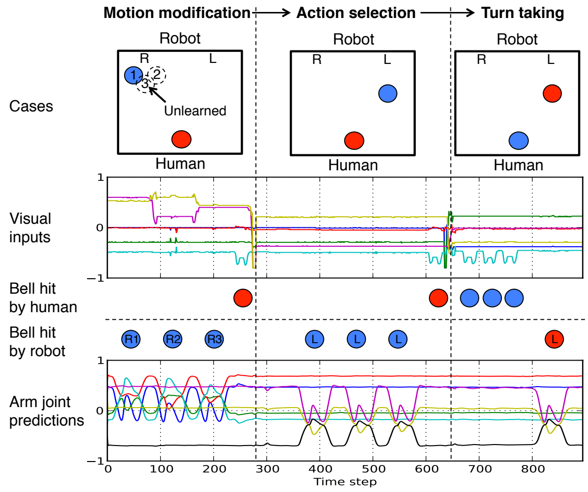

Figure 2: Testing results of BBBR task collaboration.

Acknowledgement

This work was supported in part by CREST, JST; a MEXT Grant-in-Aid for Scientific Research on Innovative Areas "Constructive Developmental Science" (24119003); a JSPS Grant-in-Aid for Scientific Research (S) (25220005); and the "Fundamental Study for Intelligent Machine to Coexist with Nature" program of the Research Institute for Science and Engineering, Waseda University, Japan.

References

[Khansari & Billard, 2011] Khansari Zadeh, S. M., & Billard, A: Learning Stable Non-Linear Dynamical Systems with Gaussian Mixture Models: *IEEE Transactions on Robotics* (2011)

[Hawkins et al., 2013] Hawkins, K. P., Vo, N., Bansal, S., Bobick, A. F.: Probabilistic Human Action Prediction and Wait-Sensitive Planning for Responsive Human-Robot Collaboration: *IEEE-RAS International Conference on Humanoid Robots (Humanoids)*, (2013)

[Awano et al., 2010] Awano, H., Ogata, T., Nishide, S., Takahashi, T., Komatani, K., Okuno, H. G.: Human-Robot Cooperation in Arrangement of Objects Using Confidence Measure of Neuro-dynamcal Systems: *IEEE International Conference on Systems, Man, and Cybernetics (SMC 2010)*, (2010)

[Yamashita & Tani, 2008] Yamashita, Y., & Tani, J.: Emergence of Functional Hierarchy in a Multiple Timescale Neural Network Model: A Humanoid Robot Experiment: *PLoS computational biology* (2008)